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Overview of Additive Manufacturing Informatics: "A Digital Thread"

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Abstract

Additive Manufacturing (AM) has huge promise for manufacturing parts with improved cost and performance compared to traditional subtractive manufacturing methods. But scale-up from prototyping operations and optimization of parts across this range of processes entails understanding complex and varied interactions between part design, materials, production processes, and part performance. To this end, significant investments are being made in R&D programs to manufacture high-performance AM parts, researching new designs and new materials. These programs generate huge amounts of data on materials, process parameters, tests, and part qualification. In parallel, many large companies are responding to competitive pressures by "digitizing" their supply chain, manufacturing processes, parts, and in-service data. Data is captured throughout the product lifecycle and analyzed for opportunities to drive down tooling costs and lead times and improve efficiencies and innovation. The phrase, "Digital Thread," is commonly used to describe this process. AM represents an ideal opportunity to apply Digital Thread (DT) technology, since 3D printing relies on new digitally - driven technologies. Success requires that data be made available to integrated discovery, data mining, and physics-based simulation tools, enabling timely evaluation of manufactured parts and ensuring a fluid response to the in-process variability that can affect part quality. This can make the difference between parts that can be reliably reproduced to the level of required fidelity (and, hence, are certifiable), as well as reducing costs of physical testing, repair, and in-service liability. Collectively, we call this AM Informatics—the science of managing AM data across its lifecycle with full maintenance of the complex relationship between the part geometry, material, and individual processes used to create the final part. This report provides an overview of the current state of AM Informatics—how data from AM is being captured and utilized to enhance supply chain and production processes, shortening development times and enhancing the reproducibility and quality of part production in support of qualification objectives.

Keywords: Digital Thread, Additive Manufacturing, Materials data management, Metadata, Data repository, Data archival, Modeling and simulation, 3D printing, Certification, AM Informatics

Introduction

The term Additive Manufacturing (AM), previously known as 3D printing, refers to a host of manufacturing operations that create solid parts by guiding the deposition of layers of material to achieve a specified geometry. Some processes use welding techniques: selective laser melting (SLM), direct metal laser sintering (DMLS), selective

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laser sintering (SLS), fused deposition modeling (FDM), and fused filament fabrication (FFF). Stereo-lithographic (SLA) processes create fusion by curing liquids, and in laminated object manufacturing (LOM), thin layers are cut to shape and joined [1]. Machines that build these parts are tailored for specific geometric, process, and material combinations. They vary in prototyping operations, cost, material options, and inclusion of in-process non-destructive testing features such as digital imaging. Post-processing steps needed to finish the part and improve its properties can involve heat treatment, surface smoothing, cleaning, and sterilization [2].

AM has huge promise for manufacturing parts with improved cost and performance compared to traditional subtractive manufacturing methods. But scale-up from prototyping operations and optimization of parts entails understanding the complex and varied interactions between part design, materials, production processes, and part performance. To this end, significant investments are being made in R&D programs to manufacture high-performance AM parts, researching new designs and new materials. These programs generate very huge amounts of data on materials, process parameters, tests, and part qualification.

In parallel, many large companies are responding to competitive pressures by "digitizing" their supply chain, manufacturing processes, parts, and in-service data. Data is captured throughout the product lifecycle and analyzed for opportunities to decrease tooling costs and lead times, while improving efficiency and innovation. The phrase, "Digital Thread," is commonly used to describe this process [3].

AM represents an ideal opportunity to apply Digital Thread (DT) technology since 3D printing relies on digitally - driven technologies. Success requires that data be made available to integrated discovery, data mining, and physics-based simulation tools, enabling timely evaluation of manufactured parts and ensuring a fluid response to the in-process variability that can affect part quality. This can make the difference between parts that can be reliably reproduced (and, hence, are certifiable), as well as reducing costs of physical testing, repair, and in-service liability.

The lofty vision of the DT requires a software infrastructure for data capture, data availability, and discovery while securing intellectual property (IP), tools for data mining, data federation and integration, quality standards, and best practices. It demands cultural shifts that ensure governance policies for data capture, platforms for collaboration, negotiation of IP rights, and controlled access to data.

Collectively, we call this AM Informatics—the science of managing AM data across its lifecycle with full maintenance of the complex relationship between the part geometry, material, and individual processes used to create the final part. AM Informatics must capture and manage all data related to the:

- Material: type, form, feed lot, and compounding effects
- Part geometry: feature variability, overhangs, CAD tools, software versions, and version control
- Processing: the parameters that control the build process, build orientation, in-process imaging and other non-destructive techniques that produce information about continually changing local conditions, and unconstrained process controls
- Post-processing: machining of surface roughness to finish near-net parts, heat-treating to improve properties or reduce residual stresses

- Testing: physical and non-destructive testing, physics-based simulation for certification
- End-of-life: recyclability, product maintenance, compliance restrictions, etc.

This paper examines the motivation for AM Informatics and the software technology needed to accomplish its objectives.

The goals of AM Informatics

The goals of AM Informatics can be summarized as the need to:

1. Understand the complex interplay of material, process, and geometry in the production of AM parts, leading to the optimization of all three variables. This opens exciting opportunities for innovation: previously unheard-of geometric parts to increase performance while lowering weight, new materials yielding novel microstructures, and improved manufacturability.
2. Improve manufacturing processes throughout the supply chain to increase efficiency and lower costs. Data gathered by connected manufacturing operations are interpreted in real time. Intelligent feedback loops enable adapting designs, materials, or processes to manufacturing and maintenance deficits [4].
3. Support requirements for part certification. AM poses considerable risk with regard to design, manufacturing and part repair, and certifiability by regulatory agencies (i.e., Food and Drug Administration (FDA), Federal Aviation Administration (FAA)) in industries where performance is critical.
4. Leverage the collaborative nature of the distributed manufacturing enterprise and government-sponsored research programs. In emerging fields such as AM, exponential growth can occur when companies leverage collective knowledge.

Key drivers for the AM Informatics platform

The need to drive innovation

Improving part design and processes requires understanding what drives part performance. Materials informatics and the way that the data is structured and distributed play a critical role in enabling the discovery of the attributes that govern specific materials behaviors. Large volumes of data potentially derived from multiple credible sources can be subject to pattern recognition and analytical techniques that can establish correlations between parameters that experimental studies cannot easily couple [5]. These techniques, which include data discovery, mining, and modeling, provide insight into how a material's composition and form, process variables, and geometric design can be optimized.

Data discovery

Data discovery tools provide engineers with intuitive data analysis methods that require minimal support from information technology departments. This “democratization” of data analytics involves software applications that enable:

- Easy-to-use, interactive visualization for exploring data relationships.
- Searching, retrieval, and comparison of structured and unstructured data.
- Integrating visualization with advanced analytics and predictive modeling.
- Use of natural-language processing with data correlation and visualization. Available offerings include IBM Watson Analytics, BeyondCore, and DataRPM [5].

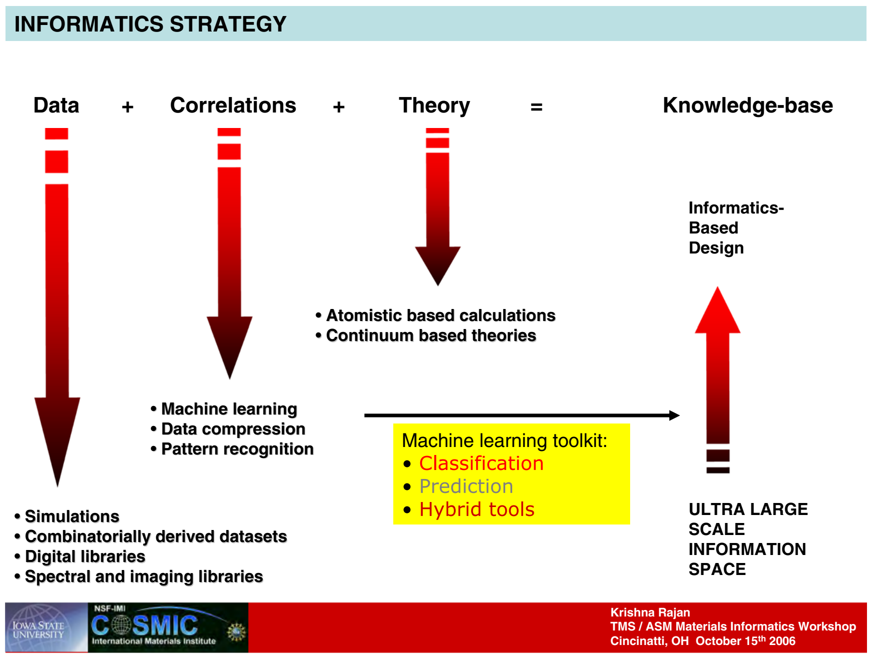

Fig. 1 Typical informatics strategy [7]

Data mining

Data mining tools use statistics, graphics, algebra, mathematics, and computer algorithms to extract meaningful information and identify patterns in collections of data [6]. Figure 1 represents an informatics strategy suitable to AM [7].

Modeling and simulation

The National Institutes of Standards and Technology (NIST), in its 2013 AM Roadmap [8], identified modeling and simulation tools as fundamental to developing and deploying AM technologies. Desired simulation capabilities include modeling residual stress direction, grain size distribution, spatial and temporal homogenization, complex lattice design, and surface finish solutions. Future, multi-scale models could support AM process selection based on key standards.

Multi-scale modeling forms the basis for predictive analysis of failure modes, such as lack of fusion, gas porosity, residual stress, and deformations. Successful modeling is, therefore, dependent on capturing data at each length scale. Results of simulation at the micro-scale eventually feed into the macro-scale models. For instance, initial data mining of test results may show relationships between the melt pool size and the beam width and flux. This provides the basis for prediction of fusion rates and, when coupled with other information, porosity and other defects that impact performance. Thus AM Informatics systems must incorporate tools that:

- Enable mining the relationships between part design, materials, and production processes to predict performance and validate those results against physical test results

- Enable visualizing directional and topological data and renderings from CAD models, in-process imaging, and simulation results

Accurate modeling and simulation requires comprehensive, validated data on materials and processes, as well as an excellent understanding of the fundamental processes and physical phenomena that underlie AM feedstock inputs, approaches, and technologies [8].

Case study: Lawrence Livermore National Laboratory A presentation by Dr. Wayne E. King at Lawrence Livermore National Laboratory (LLNL) in 2013 demonstrated a spectrum of high-performance computing (HPC) modeling and simulation capabilities, including process modeling, data mining, and uncertainty quantification (Fig. 2). LLNL draws from a "stockpile" of legacy codes that cover multiple length scales, including the well-known DIABLO code, which predicts material behavior for complex structural response and temperature-driven deformations. This has led to successful modeling of melting, solidification, and solid state phase transformations, which has been validated against literature data. Other codes predict residual stresses, identify optimum processing parameters for discrete AM powder particles, and study the effect of gravity and surface tension on melt flow. When combined with uncertainty quantification, certification of the small production lots at LLNL is becoming a reality [9].

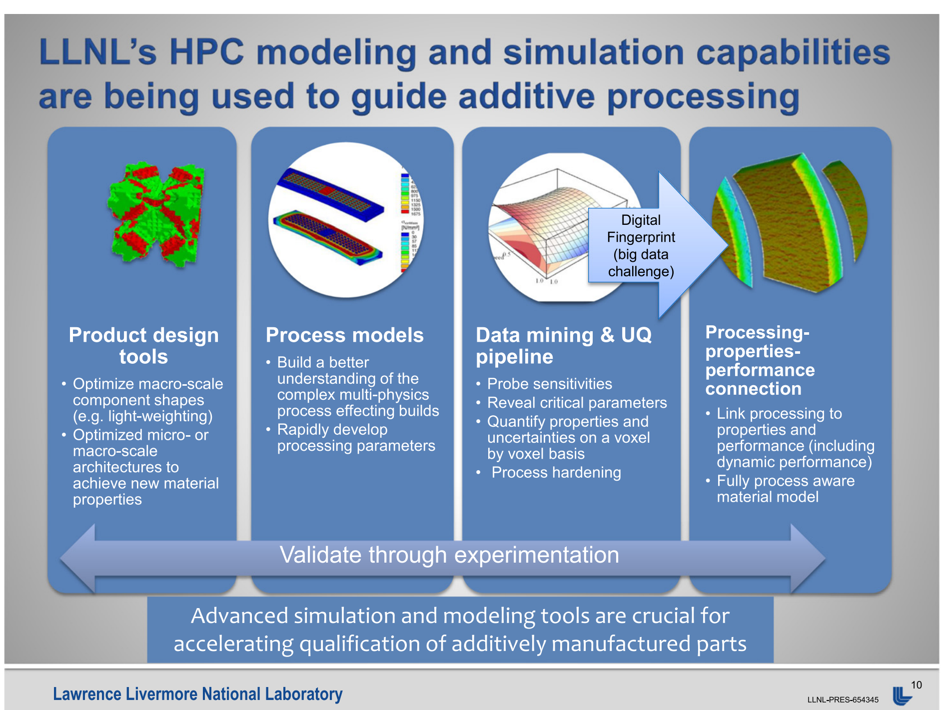

Fig. 2 Overview of LLNL's HPC modeling and simulation capabilities [9]

The need to improve manufacturing processes

The idea that data collected within the AM workflow could be used to inform the AM manufacturing process and improve efficiency or drive down cost is a DT concept. It can best be illustrated by the example of the General Electric (GE) Brilliant Factory.

Case study: the GE Brilliant Factory The Brilliant Factory, initiated in 2013 at GE, is described as a "a self-improving factory" that continuously improves products and processes with a seamless DT that gathers, analyzes, and transmits data in real time to different parts of the supply chain. Specialists throughout the process work on items simultaneously to inform decisions throughout the life of a system or product. A common database and physics-based models support design optimization for production ability, usability, and maintainability [10].

The need for certification

> A recent patent application by Boeing in support of 3D printing for replacement parts revealed there are currently 20,000 printed parts on board 10 different Boeing fleets [11].

> In April 2015, "The FAA cleared the first 3D printed part to fly on a commercial jet engine from GE." GE announced that it was working with Boeing to retrofit more than 40 GE90-94B jet engines, which power Boeing's 777 planes, with the 3D printed part—a housing for the T25 sensor [12].

Such statements indicate that AM has been used in manufacturing for quite a long time. However, with its increased use to manufacture large-scale, critical components, certification has become a widespread concern. The difficulty of certification relates directly to the complexity of the part design-process-material relationship and the effect of each on the part performance and reliability. Properties can differ significantly from similar parts manufactured by standard processes, such as casting or extrusion. For metals, there can be variability in density, residual stresses, mechanical behavior, non-equilibrium microstructures, and crystalline texture [13]. Compounding these difficulties, limited production lots make the cost of physical testing prohibitive.

Manufacturers are addressing this concern by planning new programs that start with known AM specifications (i.e., AMS 4998, AMS 499A, Rev A for direct deposition) and scaling gradually from non-critical parts to production parts, fracture-critical parts, and finally critical parts.

The National Aeronautics and Space Administration (NASA) has identified Non-Destructive Evaluation (NDE) as a group of technologies that could close the gap on measurement data at all stages of the AM lifecycle. NDE is useful in characterizing test specimens and has the potential to provide insight into the effect-of-defects on properties [14].

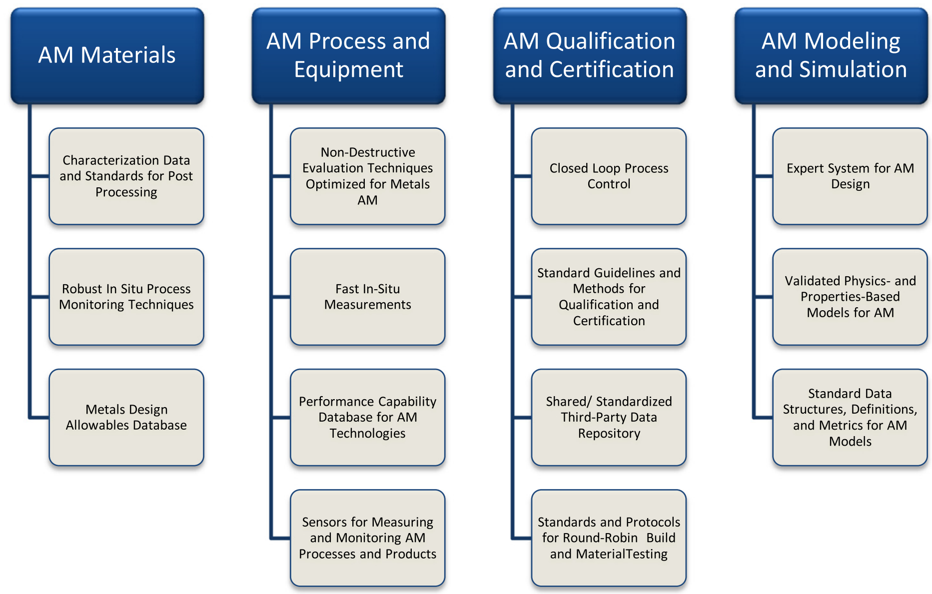

Fig. 3 NIST—important technologies and measurement challenges for AM [8]

NIST AM roadmap to certification One of the key requirements for certification is standardization. NIST has taken the lead on developing a roadmap for progressing AM by identifying the measurement barriers impeding advancement. Four primary focus areas were materials, processes, certification, and simulation. Figure 3 provides an overview of NIST's assessment [8].

Execution of the NIST roadmap, intended to produce fundamental AM standards common to AM processes and applications, will require the following development activities:

- Materials: open databases of tested material properties are needed to enable product design and establish design allowances.
- AM processes: protocols, standards, and procedures are needed to collect AM process and equipment capability data and establish a performance database.
- AM qualification and certification: standard AM material data formats and analysis methods (i.e., property extrapolation by statistical means) are needed to support an open web-based capability for publishing, clearing, and sharing data.
- AM modeling and simulation: the attributes of the various additive processes and their supporting models need to be identified, defined, and classified in a consistent way to support effective modeling and simulation tools.

NIST AM test artifact Significant to the certifying agencies, NIST has published an AM test artifact that has a representative selection of part geometries against which to validate the performance and capabilities of an AM system. The test artifact, available in both Stereo Lithography (STL) and Additive Manufacturing File (AMF) formats, can be downloaded from the NIST website along with a spreadsheet of nominal values (http://www.nist.gov/el/isd/sbm/amtestartifact.cfm). The combined part geometry and target measurement values has been submitted to the ASTM Committee F42 on Additive Manufacturing Technologies but is not yet an approved standard. However, it is immediately useful in qualifying or calibrating a build machine or refining machine parameters to compensate for machine, software, or material variability [15].

SAE International AMS-AM Committee (led by Dave Abbott, GE) The SAE International Additive Manufacturing Committee (AMS-AM) was launched to develop and maintain Aerospace Material Specifications (AMS) and Aerospace Standards (AS) for Additive Manufacturing. Specification development will target precursor material, additive processes, additive materials, post-process heat treatment, dimensional inspection, mechanical testing, non-destructive testing, and quality assurance [16].

FAA Additive Manufacturing National Team To lay the regulatory groundwork for AM technology, the FAA initiated the Additive Manufacturing National Team (AMNT). The team is collaborating with other government agencies (i.e., NASA, Department of Defense) and academia (i.e., Massachusetts Institute of Technology, Wichita State University) to assess the applicability of current FAA regulations to AM products and to develop guidelines for their safe use in a certified structure. Figure 4 [17] depicts the typical "building block test structure" used in FAA certification of aerospace structures. It provides some indication of the costs associated with certification and the difficulties to be encountered in low-volume production environments [18].

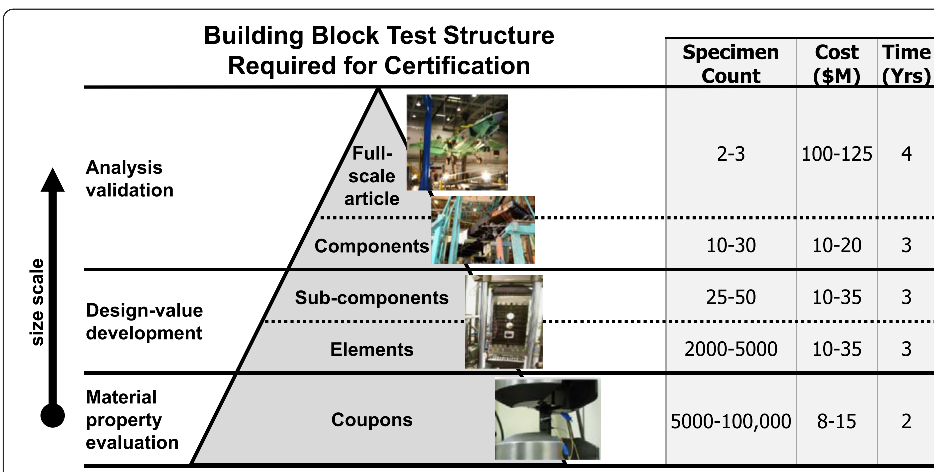

Fig. 4 Building block test structure for certification [17]

Metallic Materials Properties Development and Standardization (MMPDS) Emerging Technologies Working Group In March 2014, the MMPDS Emerging Technologies Working Group (ETWG) initiated discussions on aerospace certification. Invited speakers represented the Air Force Research Laboratory (AFRL), Boeing, Sciaky, and EMAM Systems. The decision was made to create a new section of the MMPDS Handbook to deal with engineered materials, such as those produced by AM, called, "Process Sensitive Materials." A year into its discussions within the ETWG, concepts are starting to emerge that will impact data collection and testing requirements for AM parts. Some key messages:

- The FAA seeks to develop an equivalency method using standard, certified parts (such as NIST's "build block") for part qualification. Equivalency values will be published for specific statistically valid sample sizes.
- In-process, manual, and in-the-field inspection are expected to augment equivalency methods. Digitally integrated inspection tools are needed to improve data capture in support of probabilistic analysis, modeling, and simulation.
- Noting parallels between the production of composites and AM parts, the ETWG is seeking guidance from the Composites Material Handbook Committee (CMH-17) in developing guidelines for certifying AM parts. See Fig. 5 [18].

The need to collaborate

A key requirement for supporting AM Informatics is a software platform that meets the needs of the enterprise and collaborative communities. We see this within enterprises, where AM programs must bring together R&D, part design, simulation, production, and the supply chain. We also see it across industry and governmental organizations in multi-partner projects such as the efforts for certification and

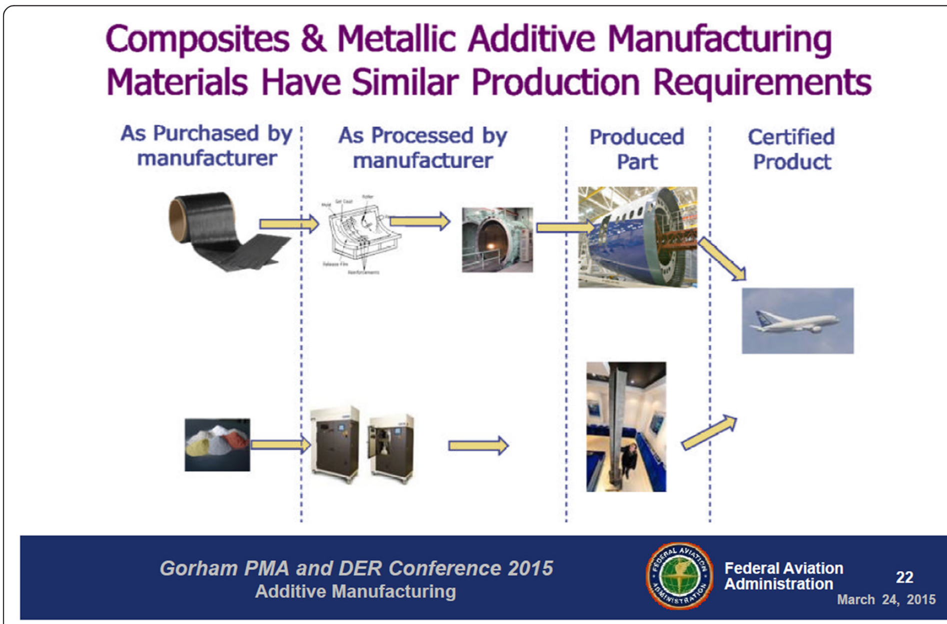

Fig. 5 Composites and metallic AM materials have similar production requirements [18]

standardization outlined above and in some of the collaborative research projects that are leading AM research efforts.

Case study: AMAZE The Additive Manufacturing Aiming (toward) Zero Waste & Efficient Production of High-Tech Metal Products project (AMAZE) is a collaborative research initiative sponsored by the Seventh Framework Program for Research and Technological Development (FP7) in the European Union. The 28 project partners from industry and academia represent a broad range of backgrounds and skills. The goal of the project is to rapidly produce large, defect-free AM metallic components up to 2 m 6 ft) in size with close to zero waste for use in the following high-tech sectors: aeronautics, space, automotive, nuclear fusion, and tooling. The four pilot-scale factories developed within the project give European manufacturers and end users a world-dominant position in AM production of high-value metallic parts by 2016 [19].

Case study: Defense Advanced Research Projects Agency (DARPA) Open Manufacturing DARPA's Open Manufacturing program seeks to advance technologies needed to implement AM in critical components and structures, provide technical assistance to the industry, and promote the potential of AM through training, education, and dissemination of information. The project supports two research facilities equipped with state-of-the-art metal processing AM machines: the Center for Innovative Materials Processing through Direct Digital Deposition (CIMP-D3) and the U.S. Army Research Laboratory (ARL) at Aberdeen Proving Ground, in Maryland, where DARPA stores its material and process data. The ARL facility provides the collaborative platform for AM data collection and dissemination [20].

Key technical requirements

The demands of AM Informatics to promote innovation, drive certification, improve manufacturing, and collaborate effectively impose technical as well as business requirements, which are discussed in the sections that follow.

Scalability and other business requirements

Data archived in support of the AM DT will quickly become "big data." The main characteristics of an ideal big data storage architecture (based on current known technologies) are discussed below [21]:

- Scalability: Data requirements are estimated from the quantity and size of files generated by integrated applications (i.e., simulations, non-destructive digital imaging). Scalability applies to data storage, transaction performance, and operations.
- Support for the data lifecycle: The optimal system stores data for high availability locally and archives the remainder at the lowest possible cost.
- 24/7 availability: Systems of backup and redundancy ensure that the data is accessible over different geographies with high performance and no downtime.

- Performance: The system must support delivery of single files to a single user yet provide the best performance for computational environments that rely on real-time movement of multiple streams of data.
- Automation: The sharing of information between applications requires an application programmatic interface (API), visual process design environment, and command line interface.
- Integration: Methods for the manual or electronic capture of legacy data in parallel with uploading new data ensures seamless migration to a new data management system. API programming options include representational state transfer (REST), C-SHARP, or Java-Script Object Notation (JSON) and must support of all user interface (UI) features.
- Integration with public, private, and hybrid cloud ecosystems: The ability to move data to and from clouds is crucial.

Data governance

The data captured in a "DT" process and collated into a database is dynamic in nature. Each interrelated facet of the manufacturing process (material, design, process, and part) has its own lifecycle and maturity level. Each bit of data describing those artifacts also has a life-cycle: data creation, acquisition, documentation, organization, migration, protection, access, and disposal. Effective management of each artifact across its data lifecycle is required to ensure that data is reliably preserved and can be accessed and used efficiently. Inadequate metadata capture (i.e., of build process parameters or a material batch specification) at an early stage of development can prevent later use; failure to migrate to new technologies can leave data inaccessible [22]. Likewise, large raw data or image files may be archived in long-term storage once analyzed data is committed to the database. For reference, Fig. 6 provides

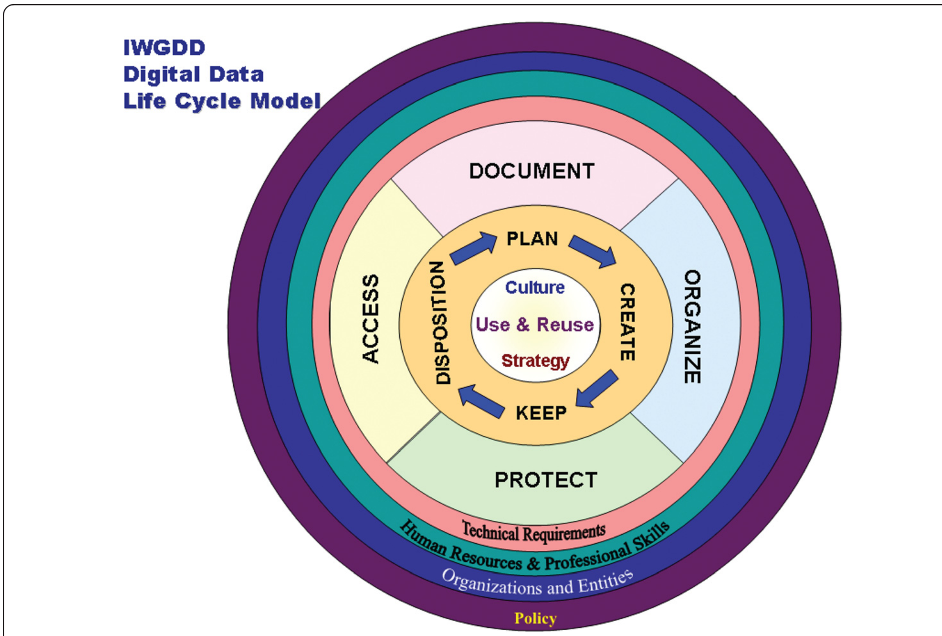

Fig. 6 IWGDD digital data lifecycle [23]

a representation of the Digital Data Lifecycle published by the Interagency Working Group on Digital Data (IWGDD), sponsored by the National Science and Technology Council to promote standards for data interoperability within science, technology, and engineering [23].

In the past, the materials lifecycle was a fairly linear process where research led sequentially through materials development, component design, component testing, certification/qualification, manufacturing, and maintenance. Newer DT paradigms interactively examine all stages of the lifecycle in parallel to ensure the shortest possible time to market [24]. An AM informatics system must be able to support the data and lifecycle retention policies of the production operation and its collaborative network or supply chain [23].

Data discoverability

> The challenge of making data discoverable is one of the most fundamental barriers to effective data sharing. [25]

Tied to the domain of data governance, key to collaboration and a driver for data schema and database architectural decisions is the concept of data discoverability. Data governance defined for a specific archive of data (i.e., derived from the digital capture of an AM project) dictates policies regarding what data is captured and stored and for how long. Data discoverability (regardless of the potential audience for the data) requires that data be archived in a manner that allows it to be selectively shared, easily located, and readily understood. For the archivist, this entails three activities [26]:

- Consistent recording of metadata
- The storage of metadata in a searchable repository
- Enabling others to search for the metadata in an efficient manner

Consistent recording of metadata

Metadata, or "information about information," provides the context for archived data. Without it, data is largely useless—and is the underlying cause of considerable research data loss. As such, the consistent recording of metadata is a direct benefit of well-documented and enforced data governance procedures.

Context can be explicitly defined or derived from the structure of the stored data. If the data is managed hierarchically, some meaning can be construed from its location within the hierarchy. Some technologies, such as those introduced by the Semantic Web, can format metadata as "triples" that ensure the data context is maintained without hierarchical data structures.

Metadata itself can be of varying types:

- Descriptive—resources for purposes such as discovery, identification, and qualification, such as the title, author, and keywords. In AM, this includes the descriptions of processes, testing procedures, or background for computational methods.
- Structural—identifies how compound objects (i.e., data tables) are put together.

- Administrative—information used to manage a resource such as file type, technical information, and access rights [27].

Searchable metadata repositories

Metadata stored in a single repository is searchable from within the repository. Collaboration within an engineering domain (i.e., AM) is facilitated by deliberately exposing metadata to outside search engines or by using metadata repositories, as dictated by the sponsoring organization. For instance, NIST correlates specific types of publications with required levels of discoverability as seen in the table below [28].

Discoverability level	Requirement	Publication type
1	No discoverability requirements.	Working data, derived data
2	Metadata values must be entered into the NIST Enterprise Data Inventory and a Persistent Identifier (PID) minted for the dataset.	Publishable results
3	Metadata values in the NIST Enterprise Data Inventory are made publicly accessible.	Published results, resource data, reference data, SRD

If the metadata is to be exposed, storing it in a dedicated repository can simplify its management and facilitate search and retrieval. Metadata stored in a separate repository is linked to the objects it describes. The most commonly used metadata repositories are listed in the table below.

Repository	Description
Dublin Core (DCMI)	An open organization supporting innovation and best practices across the metadata ecosystem [29].
DataCite	Works with data centers to assign persistent identifiers to datasets and other research objects to support citation, discovery, and access. They leverage the Digital Object Identifier (DOI) infrastructure and provide worldwide location services for repositories via re3data.org [30].
RDA Alliance	The Research Data Alliance (RDA) works to build social and technical bridges to facilitate data sharing and re-use. Operates through a network of Working Groups that target specific communities of practice [31].
Digital Object Identifiers ("DOI")	DOI services provide registration authority for persistent interoperable identifiers of physical, digital, or abstract objects for use on digital networks. Uses an identifier syntax and network resolution system called a "Handle System®" [32].

Controlled and efficient metadata access

Visibility into a data archive is a highly sensitive topic, as for most companies AM research represents potential competitive advantage. Exposing even the metadata can provide insight into valuable IP. The digital framework hosting an AM data archive must provide a means of controlling access to all data, including metadata. Once accessed, metadata can be retrieved using the query and analytical tools of the core platform.

Architectural decisions

With an understanding of the technical requirements, architectural decisions can be approached. Primary is consideration of the target community—e.g., whether the AM Informatics platform serves internal corporate research efforts or collaborative research projects. Corporations typically host within their corporate intranet. Cross-sector collaborations (i.e., government, education, research, and non-profit institutions, across regions and countries) are typically hosted on the cloud by third party vendors.

Single database repositories

Single database, repository-based, *N*-tier client-server architectures (Fig. 7) are deployed in most data management systems, including commercial and open-source products. In this architecture, the presentation, data processing, and data management functions are separated, enabling greater flexibility in their development and maintenance. External access to the data relies on API integration or flat file formats, where the data exchange protocol conforms to the data model/schema that structures the data. Integration with Semantic Web technologies is possible, enabling inclusion of single database architectures within federated database systems [33].

Federated systems: multiple database repositories

In cases where a project has many partners or a company has legacy databases, there is the option to leave those applications as self-governing entities while making data available from a single query-able interface. This eliminates the need for data migration to a single-repository. These "federated" systems are among the most difficult to develop and support, as they rely on full API integration, in which the federated databases all

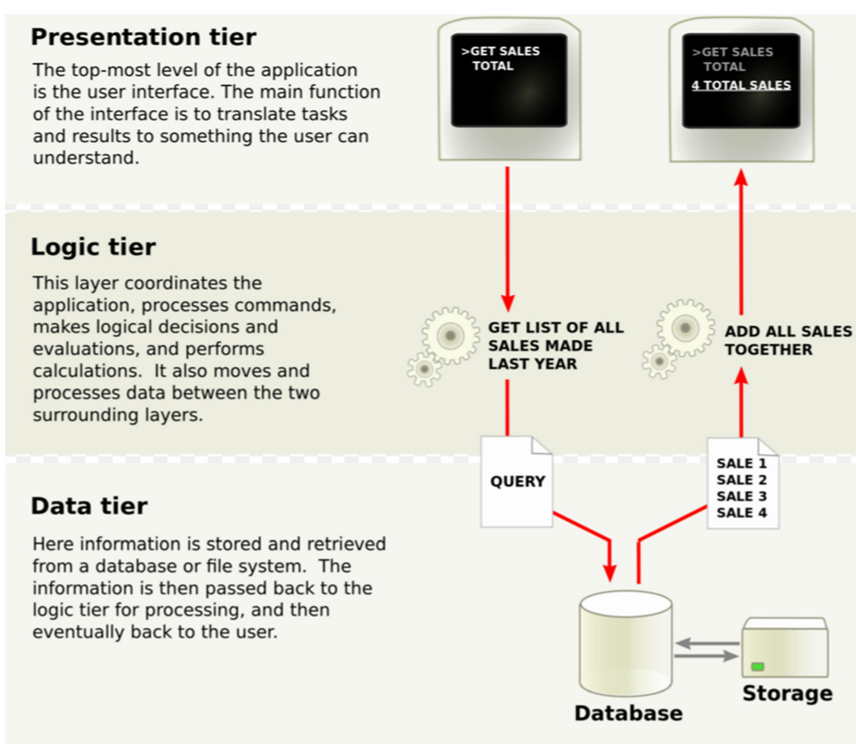

Fig. 7 Visual overview of a three-tiered application [53]

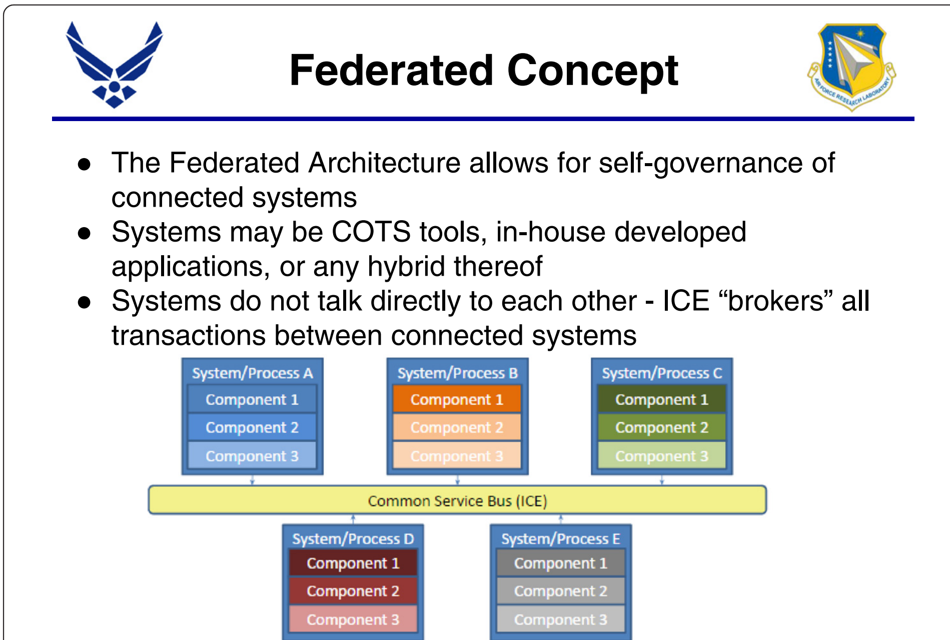

Fig. 8 Overview AFRL ICE architecture [34]

support standard calls for request and return. Successful implementations rely on each federated database to support:

- Searching across repositories to retrieve results in different groups
- Exposure of metadata for identifying database content
- Communication framework for contacting data owners to obtain access to archived data
- Neutral data exchange formats, such as Semantic Web technologies or XML

An excellent example is AFRL's Integrated Collaborative Environment (ICE), an implementation of HubZero (www.hubzero.org). Its goal is to deliver materials data efficiently to 700 scientists using 80+ engineering software applications in 200 laboratories. Its federated architecture, illustrated in Fig. 8, uses a Common Service Bus (ICE) to connect self-governing database systems. ICE "brokers" all transactions. Key software components include the GRANTA MI Materials Data Management System, Django, plot.ly, graphical workflow design tools and Digital Object Identity Management. As a fully federated system, it relies on REST API connections to all systems in support of the underlying Semantic Web technologies [34].

AM Informatics tools

The previous sections inform the requirements for developing an AM Informatics platform. While many of these requirements are common to materials data management systems, additional demands derive from the need to provide data traceably to an evolving range of design, manufacturing, testing, and simulation tools. This translates into the following critical features of an AM Informatics platform:

- A database system with scalable architecture that captures variable volumes of data with different governing policies for archival purposes.
- A flexible data schema that supports the management of data and metadata for widely differing materials and processes at all the required length scales. Additional data field tags may be required for linking a static database to a DT.
- An interface that supports manual and automated processes (via API connection or command line interface) for data capture from materials testing machines, CAD design software, AM build machines, post-processing operations, and NDE part inspection processes.
- The ability to interrogate stored data to mine the material-process-performance relationships, export to data discovery and mining tools, simulation tools, and common applications, such as MatLab and Microsoft Excel.
- Graphics tools that enable visualization of directional and topological data and renderings from CAD models, in-process imaging, and simulation results and optionally validate predicted performance against physical test results.
- A security model that protects sensitive IP and enables users in different roles within the manufacturing operation and supply chain to access the data they need.

The following sections discuss software tools that support these features.

Repositories

As noted earlier, there are two types of enterprise architectures: single database repositories and federated systems. Underlying both architectures is a database. The ability to meet the demanding requirements of the enterprise or hub relies heavily on the characteristics and robustness of that database. Some commonly used, enterprise-scalable databases include MySQL Database Server, Microsoft SQL Server, Oracle, and PostgreSQL.

Schemas

AM represents a community of practice that has very specific data collection requirements. Agreement of an ontology (or schema) to support the entire lifecycle of an additively manufactured part at any phase of maturity from research to full production systems is a prerequisite to data collection. Some level of standardization for data exchange is required to promote collaborative efforts, data consolidation, and the eventual drive toward certified parts.

As with all schema development activities, the initial step involves driving consensus on the actual data that needs capturing. It will take research to understand the impact of specific inputs and variables on part quality. Therefore, the AM schema must contain virtually all variables of the materials and processes which can be captured. It is expected that the AM ontology will change as AM materials, processes, and testing methods are refined or entirely new AM systems are created. The ease of modifying a populated schema will vary with the underlying database technology. A highly structured database will be more difficult to modify than a Semantic Web technology. Neither system is static with regard to data storage, regardless of schema design. If a data element is no longer required to capture an AM material or process, it is simply not populated.

There have been several attempts to create an AM schema originating with different organizations and projects, the schematics of which can be seen in Fig. 9.

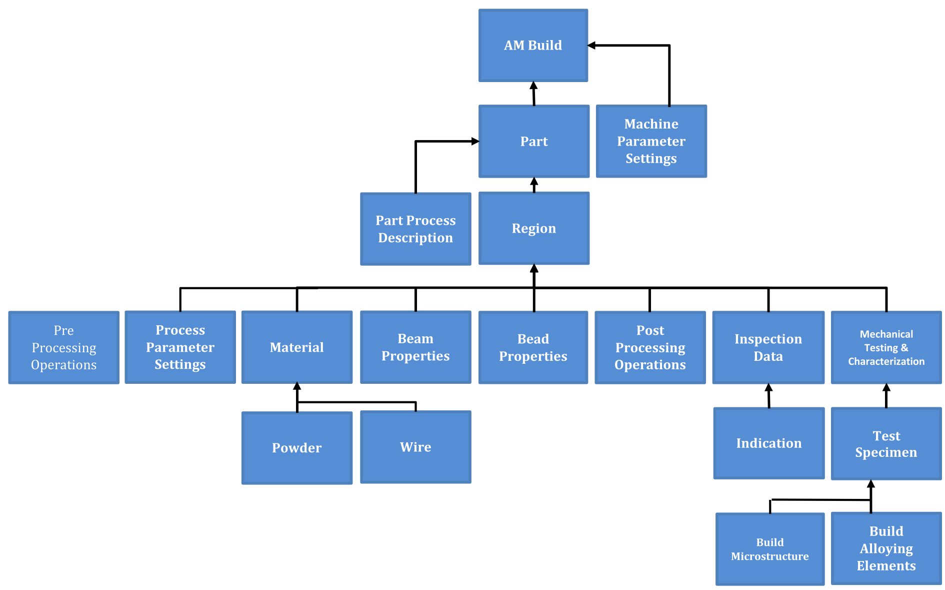

Fig. 9 DEDatabase data definitions [35]

Figure 9 provides an overview of the data relationships defined for the DARPA-sponsored DEDatabase [35].

The schema illustrated in Fig. 10 was developed for a DARPA Open Manufacturing project by Materials Data Management, Inc. (MDMi) in conjunction with Army Research Laboratory (ARL) [36].

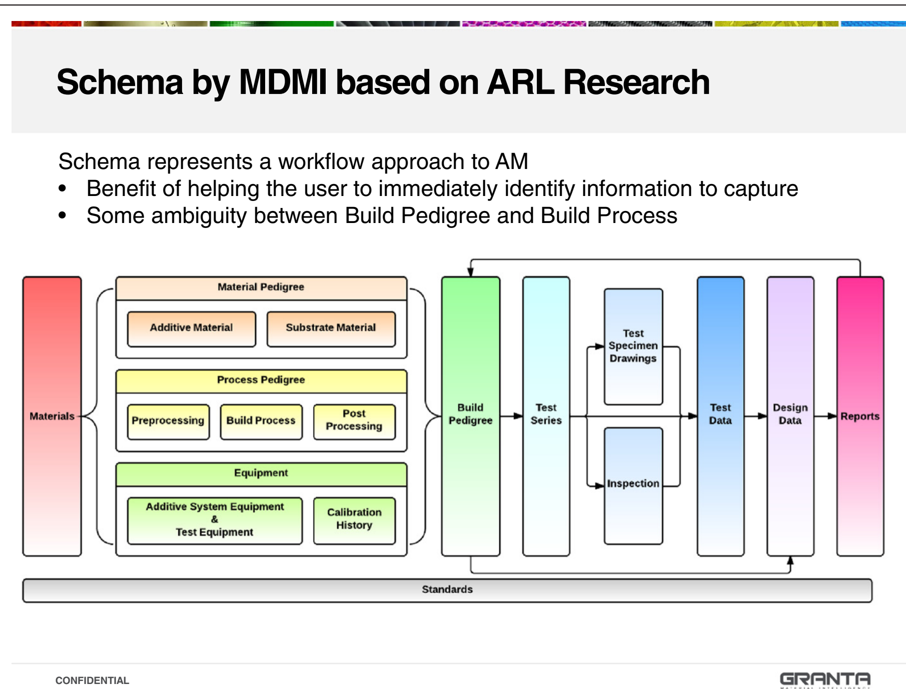

Fig. 10 Research Additive Manufacturing schema DARPA [36]

Layout Headings - Granta AM Schema v1.01					
Machines	Materials	Part Design	Material Batches	Builds	Parts
General Information	General Information	General Information	Project Information	Project Information	Project Information
Calibration	General Properties	Original Design	General Batch Information	General Information	Part Information
Machine Specifications	Composition overview	Re-Design	Manufacturing	Build Information	Part Specifications
Material	Bulk Mechanical Properties	Dimensions	Material Quality	General Build Parameters	Samples
Machine Properties	Bulk Thermal Properties	General Material Properties	Particle Properties and Size Distribution	Build Atmosphere	Visual Inspection
Build Environment	Bulk Electrical Properties	Processing	Interstitial contamination	Material Used	Accuracy Testing
Laser Properties	Biological	Static Tensile Properties	Flowability	Support	NDT Testing
Electron Beam Properties	Chemical	High-cycle fatigue properties	Wire Properties	Filament Information	Post Processing
	Eco	Fracture Toughness	Chemical Analysis and Composition	Substrate	Heat Treatment
	Cost	Fatigue Crack Growth		Quality of Welding Consumables	HIP
	Safety and Handling	Surface Roughness Requested		Build Alarms	Machining
	General Information	Other Requested Properties		Themes Used	Laser Polishing
	Requirements	Final Part Details		Powder Build Parameters	Other Post Processing
	Composition	Quality Assurance		Wire Build Parameters	
	Physical Properties	Key Benefits		Laser Properties	
	Further Information			Electron Beam Properties	
				Arc Properties	
				In-Process Rolling	
				In-Process Analysis	

Fig. 11 Sample of attributes in AM schema tables [38]

Granta AM schema Granta Design, working with the Material Data Management Consortium (MDMC) AM Subcommittee, drawing from experience within US Government-sponsored projects and the European Union AMAZE project, released its first version of a comprehensive and highly configurable AM schema implemented within Granta MI in 2015 [37]. It includes over 800 attributes distributed over an AM

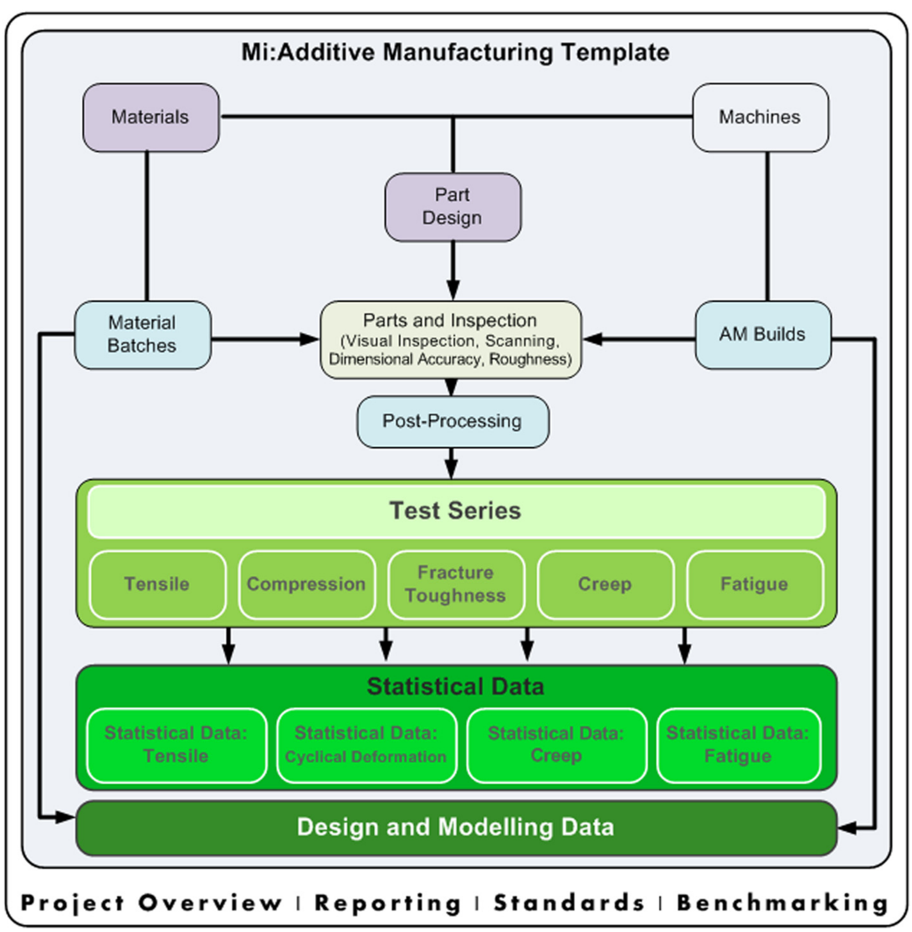

Fig. 12 MI:Additive Manufacturing schema layout [38]

ontology represented by 21 tables for seven manufacturing stages. Figure 11 provides a listing of the categories for the attributes found in the main tables of the AM schema. Figure 12 illustrates the general layout of the AM schema, highlighting its focus on maintaining the relationships between the material, part and process, and subsequent physical and virtual testing. This ensures full traceability of the data flow from raw material testing through part design, material characterization, manufacturing, post-processing, physical testing, and simulation. Validation is progressing rapidly as AM Subcommittee members adopt the schema for their own research and manufacturing efforts [38].

What remains to be completed is a definition of the attributes implemented in the schema, so that data values associated with the defined attributes can be meaningfully communicated to another user. A growing consensus among early adopters will provide the foundation for moving the schema toward the standards community for integration with, or enhancement of, existing standards such as ASTM F42, MatML (or similar XML-based technologies), or the development of new standards.

Point of data generation capture

> 47 % of manufacturers surveyed indicate that uncertain quality of the final product was a barrier to the adoption of AM – capture of the complete part pedigree will be critical to product acceptance [39].

What to capture?

AM is an evolving manufacturing process that is still highly subject to R&D. The collaborative nature of much of this work poses some very real problems to a project that is not subject to data retention policies:

- It introduces the opportunity for inconsistencies that, without systematic data capture, could make manufacturing reproducible parts nearly impossible.
- Collaborative R&D programs generate high volumes of complex data (stored in machine log files, Excel, Word, PDF…) that end up distributed across partner organizations or individual projects.
- Because project data is rarely aggregated or collated, opportunities are missed to capitalize on the collective value and work may be duplicated.
- Because data is not retained and used, investments in projects rapidly depreciate once the project is concluded [40].

Funding bodies are increasingly mandating plans and infrastructure to retain data and knowledge, which is identified in project governance policies. The general consensus is to capture all data generated by the manufacturing process and in-process and virtual or physical testing. At later stages of maturity, the decision to archive may be influenced by the data type, its context, and how easy or costly it is to reproduce if needed in future projects.

Some artifacts generated by the AM manufacturing process, such as the digital representations for requirements definition, conceptual design, detailed design, development, production, in-service, and end-of-life, are traditionally archived in enterprise product management systems such as SAP, ERP, or PDM. These management systems can be used to systematically inform the next step of the process, if fully integrated. Informing these systems may or may not be part of the workflow associated with an AM data system but may be relevant to the DT.

Data capture workflow

Within a specific manufacturing process, such as the workflow that comprises the creation of an additively manufactured part (Fig. 13 by EWI), the data often literally “flows” from one process step to the next [41].

Capturing the data as the process step is executed ensures the correctness of part pedigree and supports “zero” data loss concepts. Implementing minimally invasive data capture procedures, zero cost of data capture, can increase compliance with governance policies. The optimal data entry tools (manual or automated) depend on the method of data generation, the size of the file, and whether the data is suitable in its current state (i.e., raw test data or AM build files) or needs to be cleansed and analyzed. Raw data files can be indexed within the database and stored on a drive for retrieval if required for review or further analysis.

Data which requires manual capture can be entered into a simple-to-use electronic interface (i.e., Fig. 14) that automatically uploads values to the AM database. This semi-automated process can streamline data capture from the shop floor, research lab, or test lab. Both structured and unstructured data in Excel or text files can be uploaded through web browsers via drag-and-drop interfaces [38].

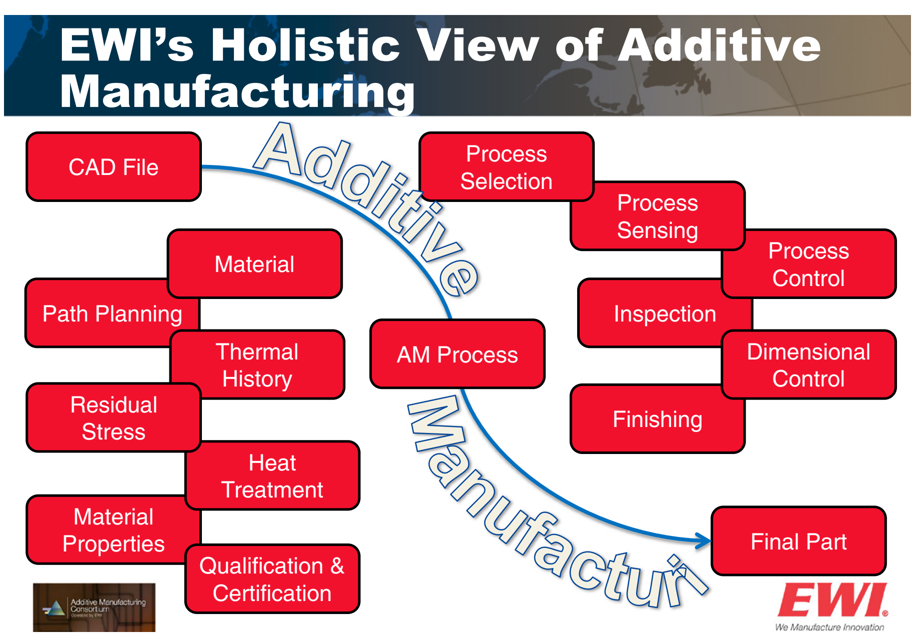

Fig. 13 EWI’s holistic view of Additive Manufacturing workflow [41]

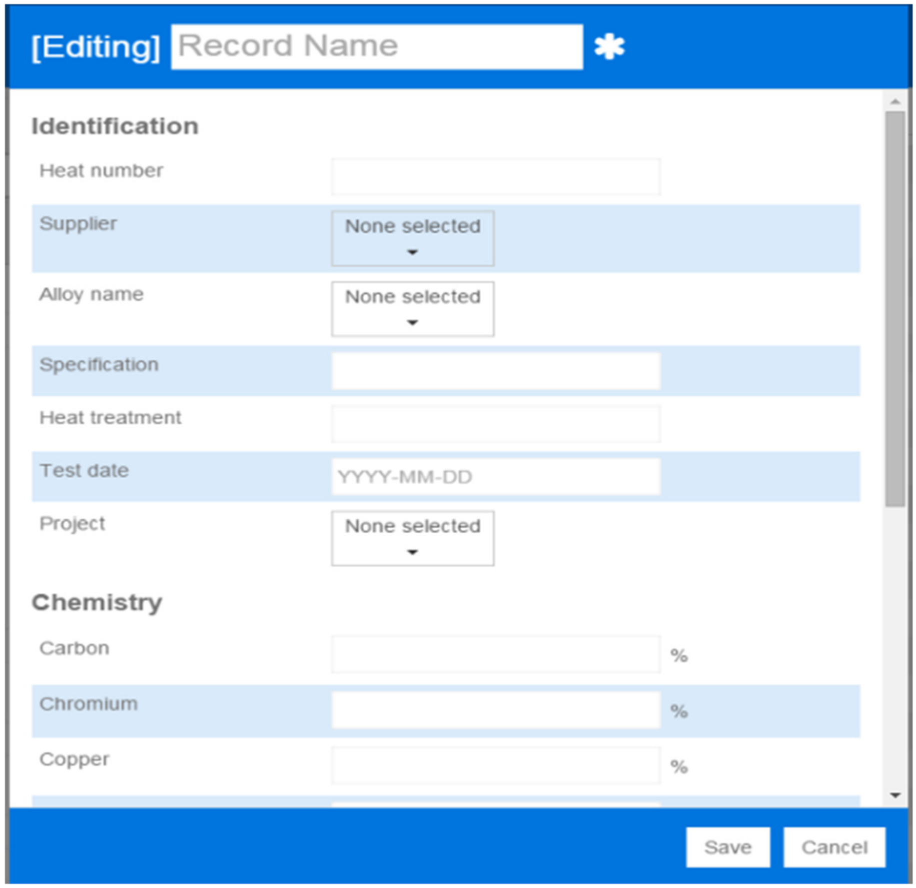

Fig. 14 GRANTA MI:Explore edit interface [38]

Automated capture can be facilitated via API integration or through systems of barcoding, which enable direct upload via scanning/imaging techniques. API integration is suitable for bi-directional data transfer between materials testing machines, CAD design software, AM build machines, post-processing operations, NDE part inspection machines, simulation software, and common applications, such as MatLab and Microsoft Excel.

The inputs and outputs of tools, including CAD drawings, simulation results, and build files, become very much more useful when imported to a database management system. The resulting fusion of experimental and process data (whether from actual build logs or generated by simulation models) can dramatically accelerate knowledge of processes, materials, and components and enable uncertainty quantification. A simple example is demonstrated in Figs. 15 and 16. Figure 15 displays the variability of laser temperature over the course of a Renishaw build, as extracted from the Renishaw log file. In Fig. 16, AM build data (i.e., travel speed) is combined with physical test data to identify the effect of laser speed on the ultimate strength of a part. This type of cross-comparison between a process parameter and test result can easily be applied to any physical, virtual, in-process, or microstructural testing *for a single AM system* [38].

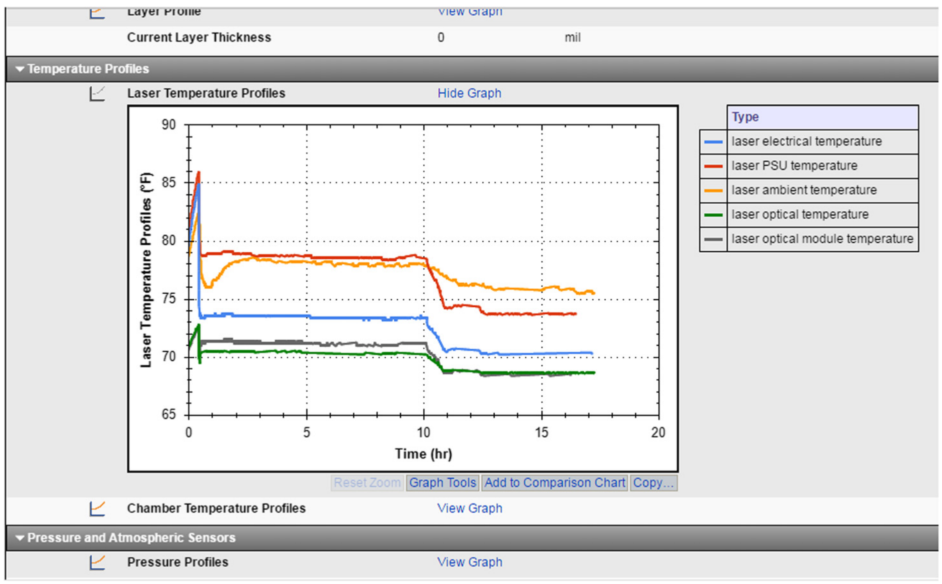

Fig. 15 Image capture after import of Renishaw build file [38]

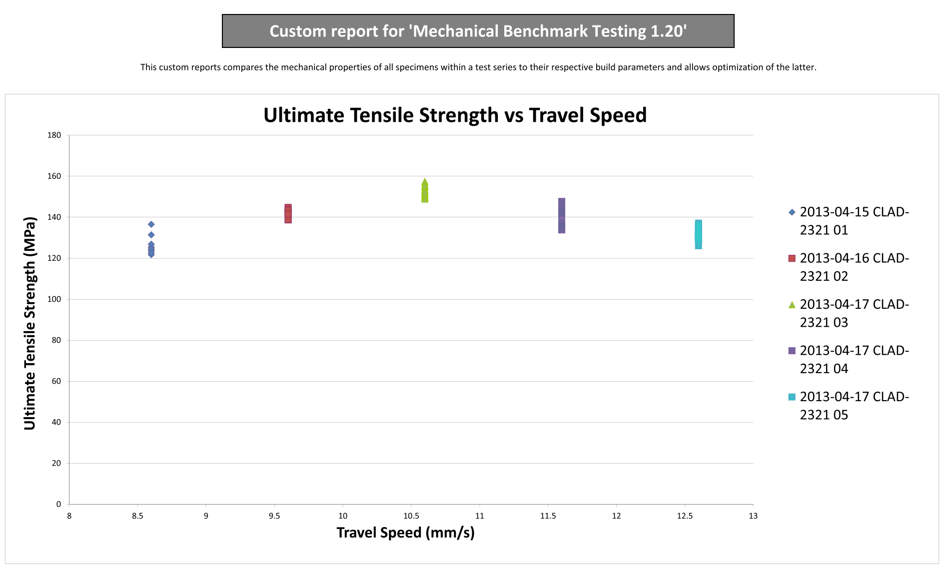

Fig. 16 Data discovery—ultimate strength vs. laser travel speed [38]

Discovery and data mining tools

The following section covers the spectrum of data analytics available for use in AM Informatics.

Data discovery tools

At the opposite end of the spectrum from complex simulation lie methods for data discovery that help answer diagnostic questions, such as why something happened. The most common data discovery tools are Excel and query languages. It is a good idea to formalize the analysis functions for which these tools are commonly used within a database interface. When backed by an approved set of data, engineering organizations can then ensure that the insights gleaned are consistently generated and can be communicated effectively throughout the enterprise.

Most data discovery tools have a common set of core capabilities:

1. An easy-to-use and feature-rich interface that is intuitive, accessible to users with minimal training, visually compelling, capable of offering a range of direct interaction with the data, and capable of information transformation, rendering, filtering, and analysis
2. An in-memory engine to provide decent performance for interactive information exploration
3. Data connectivity enabling access to multiple data sources without IT support:
   - User-driven data sources, such as Excel and comma-separated values (CSV) files
   - Corporate-managed materials and engineering data sources
   - External data sources, such as open data sources from information providers, structured or unstructured. More advanced tools enable blending data in a visualizations or analysis [6]

Case study: GRANTA MI:Explore GRANTA MI:Explore, Fig. 17, provides an excellent example of a discovery tool designed for use in materials engineering. It allows users to quickly find the information they need and filter, compare, and plot data. In Fig. 17, a few mouse clicks enable plotting of variables for a wide selection of materials, zooming in on a region of interest, selecting a single material, and viewing its datasheet [38].

Modeling and simulation tools

Modeling and simulation tools for guiding optimization of the AM process are increasingly available, both commercially and via government-funded research progress. The data requirements are quite rigorous, as they are highly dependent on the thermal

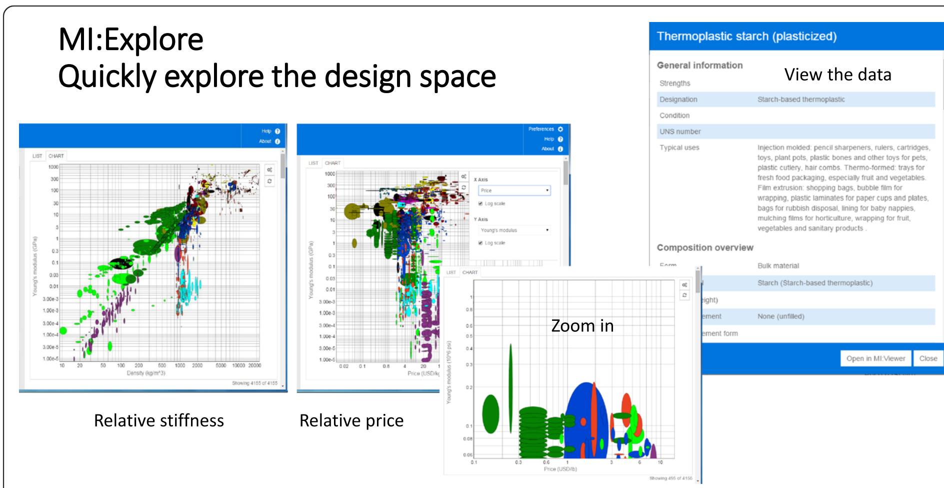

Fig. 17 Data discovery tools—GRANTA MI:Explore [38]

profile for material properties. Integration with the AM platform ensures consistent and repeatable results. Some strategic partnerships have recently formed to accelerate development. 3DSim has partnered with UL Laboratories and Dassault Systemes partnered with Safran, both in the June 2015 timeframe.

Commercial tool—3DSim 3DSim (www.3dsim.com) is a commercial software enterprise that seeks to "move AM from empirically driven models to simulation-driven models" to accelerate the certification of AM parts and processes. They have developed two solvers that approach the problem of predicting part performance. A process solver uses in-process measurements to predict properties of the part structure (i.e., phase transformations, residual stresses, and cooling rates), while the material solver uses the material structure to predict the performance of the part. 3DSim technology features an efficient meshing technique that has improved the speed of multi-scale finite element analysis by a factor of 3000 over traditional FEA methods, making it a viable option for real-time process monitoring. It is undergoing validation through projects sponsored by America Makes, Rutherford Appleton Labs, and DARPA Open Manufacturing [42].

Open-source tools Government-funded projects are driving new research to develop open-source models for simulating AM processes. Some recent activity:

- America Makes recently funded a joint project between GE and LLNL to develop open-source algorithms for optimizing AM metal parts produced by SLM that leverages LLNL's HPC cluster and expertise in lasers. The project seeks to develop software algorithms compatible with all 3D printers that produce metal parts to optimize the thermal characteristics for each layer by controlling the scan laser's parameters, such as beam size, scan rate and power, the powder characteristics, and the part geometry [43].
- NSF recently awarded funds to "Multiscale Structure-mechanical Property Investigation of Additive Manufactured Components for Development of a Reliable Qualification Method" and "Automation Tools for Modelling AM Process of Complex Geometries in ABAQUS". The RAMP grant will enable to developing computer codes that automate the finite element simulation of certain AM processes and material [44].

Current applicable solutions

The following section reviews a sampling of open-source and commercial software platforms possessing an architecture that *uniquely* addresses the requirements of an AM Informatics platform. This list is intended to be neither comprehensive nor a recommendation for any particular system. However, unless proven to support AM data in the context of company-funded or government-sponsored projects, it cannot be assumed that a given solution is reasonably complete. Conspicuously missing for most solutions is the lack of an AM ontology, a situation which could change rapidly if a standard ontology were introduced into the AM domain.

Open source

NIST DSpace repository DSpace (www.dspace.org) is a cloud-based, open-source repository developed by NIST for archiving publicly accessible engineering project data. The JAVA-based source code is distributed via GitHub (www.github.com) and can be compiled on Windows or Linux. It provides a workflow for the upload and management of materials data that automatically assigns a unique data citation, persistent identifier, usage licenses, and distribution agreement. All data types common to engineering are supported. Both open and closed access protocols are supported. Materials data stored to DSpace is discoverable by search engines [45].

MatOnto iNovex, funded by Small Business Innovation Research (SBIR) grant, in collaboration with Penn State University, the University of Queensland, and Cambridge Semantics, has developed MatOnto [46], an open database for support of global materials research. MatOnto, uses a web-based, distributed infrastructure and a top-level domain ontology as the foundation for a Semantic Web of materials resources. It converts standard database constructs such as metadata and schemas into semantic links [46], provides web addresses for every data point, and converts Structured Query Language (SQL) into Resource Description Framework (RDF) formats. Standard ontologies will be required to ensure meaningful queries into the data, but variable metadata formats are supported [47].

GE's Digital Manufacturing Commons GE is leading an effort to develop an open-source, online community for collaboration and data analytics in support of the supply chain that services DT manufacturing operations. The open-source platform GE scientists are developing builds on the successful platform they demonstrated in a DARPA-funded project with the Massachusetts Institute of Technology (MIT), which has been recognized as an outstanding innovation by top manufacturing leaders. Its goals are to democratize access to tools within organizations supporting DT. The platform will feature a distributed and federated architecture that can support the data flow between participants within the manufacturing process and supply chain [48].

DARPA VehicleFORGE The VehicleFORGE platform is a web-based, collaborative design environment based on the concept of modern-day software "forges" (e.g., SourceForge, forge.mil). VehicleFORGE was developed within the Adaptive Vehicle Make (AVM) program to provide a common platform for design. It is also a portal for accessing design tools, manufacturability tools, component models, and generated system designs. VehicleFORGE was developed with an extensible architecture that allows plugins to be developed for specific tasks. To date, plugins exist for CAD visualization, project design trade space exploration, and scoring analysis based on virtual testing. The VehicleFORGE platform, hosted on a private cloud at Vanderbilt University, is highly scalable, fault tolerant, and flexible [49].

Commercial solutions

The ASM CMD network ASM International founded the Computational Materials Data Network (www.cmdnetwork.org) in 2012. Based on a single-repository enterprise architecture, GRANTA MI, it has hosted several materials projects that have developed, curated, and managed materials data aggregated from a range of sources. One example is the NIST-ASM Structural Materials Data Demonstration Project (SMDDP), a collaborative effort in support of AM process optimization that includes participants from NIST's Material Measurement Laboratory, ASM International, Kent State University, Georgia Tech, Materials Data Management, Inc. (MDMi), Granta Design, Ltd., Nexight Group, Mercury Marine, and Alcoa. The SMDDP project is developing an open demonstration database for metallic structural metals. In its initial phases it is focusing on Aluminum 6061 and the thermal and mechanical properties of its underlying ternary system, Al-Mg-Si [50].

Granta Design (and its work with AMAZE and DARPA) Granta Design produces a commercial materials database system, GRANTA MI, which specifically targets the AM space with its GRANTA MI:Additive Manufacturing package. GRANTA MI derives from 20+ years of managing materials information for the design and analysis communities of leading engineering enterprises in Europe and the US. Its architecture addresses the main objectives of DT initiatives, including those that specifically target AM parts.

The GRANTA MI platform is well tested via some very large collaborative projects, including the AMAZE project, a complex, multi-partner, and multi-national project. GRANTA MI provides the collaborative materials platform for this project, managing the data, access rights, and protecting IP of the individual participants. Driven by an AM-specific schema, it enables the capture of data and maintains the critical links between alloy composition, powder and wire production, additive processing, microstructural evolution, defection formation, and the performance of metallic AM parts. These in turn are used to validate multi-level process models and predict part quality.

The experience of AMAZE helped to inform development of the GRANTA MI:Additive Manufacturing software package. This package is an attractive option for companies wanting to bid for government-funded initiatives, as both the solution and price are well-defined [51].

GRANTA MI has been installed under guidance of Materials Data Management, Inc. as the data management platform in support of a DARPA Open Manufacturing project. The first iteration of the schema for capturing AM material, process, and test data was generated by this project [52].

Conclusions

Additive Manufacturing aligns well with DT concepts, requiring the systematic capture of digitally generated material, process, and in-process non-destructive testing and physical testing data. Capturing this data offers significant advantages to the manufacturer who is committed to producing high-quality, certifiable parts. For instance, in-process capture of non-destructive testing (i.e., imaging) when combined with the latest simulation techniques offers the possibility of responding to potential part failure modes in real time. There is further opportunity to repurpose that data for evaluating an Additive Manufacturing operation to identify waste, inefficiencies, supply chain risk, and other business parameters that affect profitability.

While AM standards and certification are in the early stages of development, an AM Informatics solution using a vetted AM schema and the flexibility to adapt quickly to changes in processes, materials, and conditions can help to deliver the potential of AM to drive down development times, cut costs, and increase innovation. Industry collaborations, typically initiated by government-funded projects, have great potential to drive AM forward—particularly in the area of standards development. Selection of an AM Informatics platform should be made with the intention of supporting collaboration to ensure compliance with project policies.

An AM Informatics platform that can support the lofty goals of DT, is in most cases only a moderate extension of existing materials data management technology. Federated systems are more difficult to implement due to demanding integration requirements and the need to leverage semantic links or commercial metadata applications to ensure discoverability. Some, however, are built on open-source models that may allow for software extension where in-house skills exist to support the development activity. Mature, single-repository systems, configured for managing Additive Manufacturing data, are commercially available and proven to handle collaborative AM workflows, while enabling the data discovery and analytics required to progress an AM initiative.

Competing interests
The authors are employees of Granta Design, Ltd.

Authors' contributions
DM wrote the main portions of the manuscript. SW and WM provided the critical review, feedback, and complimentary perspectives. All authors have read and approved the final manuscript.

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References
1. Thomas Reuters (2014) Data citation index., Thomas Reuters, http://thomsonreuters.com/data-citation-index/. Accessed 28 August 2014
2. Hoffmann, T (2015) Your airplane is ready to print. In: FAA safety briefing, May/June, 54(3), pp 17-19. http://www.faa.gov/news/safety_briefing/2015/media/MayJun2015.pdf. Accessed 19 September 2015
3. Redmond and UI Labs (2014) Agreement for Digital Manufacturing and Design Innovation Institute, Chicago. U.S. Army., http://s3-us-gov-west-1.amazonaws.com/www-production/documents/Cooperative-Agreement-Release-7-17-2014.pdf. Accessed 11 September 2015
4. Pike J (2015) Are you ready to join the Digital Thread revolution. In: Aerospace Manufacturing and Design., 24 April 2015. http://www.onlineamd.com/article/amd0415-digital-thread-technology. Accessed 19 September 2015
5. Tapadinhas J, Sommer D (2014) What data discovery means for you., Gartner, Inc. Available via DIALOG. http://www.gartner.com/technology/reprints.do?id=1-2BHBA5H&ct=150310&st=sb. Accessed 21 September 2015
6. Rajan K (2008) Materials Informatics and data mining. In: Society for industrial and applied mathematics., p 2, 24 September 2008. https://www.siam.org/news/news.php?id=1422. Accessed 19 September 2015
7. Rajan K (2006) Data mining and materials informatics: a primer., Presented at TMS/ASM Materials Informatics Workshop, Cincinatti, 15 October 2006. Accessed 19 September 2015
8. Jurrens K (2013) Measurement science roadmap for metal-based Additive Manufacturing, s.l.: energetics incorporated. Proceedings of roadmap workshop on measurement science for metal-based Additive Manufacturing, NIST Campus, Gaithersburg, December 4-5, 2012., pp 6–41, http://www.nist.gov/el/isd/upload/NISTAdd_Mfg_Report_FINAL-2.pdf. Accessed 19 September 2015
9. King W, Anderson A, Ferencz R, Hode N, Kamath C, Khairallah S (2013) Challenges and opportunities: 3D modeling and simulation (p.2) Lawrence Livermore National Laboratory. Presented at Additive/Aerospace Conference sponsored by Infocast, October 16-18, 2013, Los Angeles., Accessed 20 September 2015
10. Kellner T (2015) Personalized production: the Brilliant Factory will match the right parts with the right tools. In: GE Reports., Available via DIALOG. http://www.gereports.com/post/114774680705/personalized-production-the-brilliant-factory/. Accessed 17 September 2015
11. Boeing (2015) TCT accelerating 3D technologies—Boeing patent. In: TCT magazine + personalize., Available via DIALOG. http://www.tctmagazine.com/3D-printing-news/boeing-files-patent-for-3d-printing-aircraft-parts/. Accessed 12 September 2015
12. GE Reports (2015) The FAA cleared the first 3D printed part to fly in a commercial jet engine from GE. In: GE reports., http://www.gereports.com/post/116402870270/the-faa-cleared-the-first-3d-printed-part-to-fly. Accessed 17 September 2015

13. Wraith M (2015) Printed metal parts meet critical national needs., Lawrence Livermore National Laboratory Manufacturing. https://manufacturing.llnl.gov/additive-manufacturing/metal-additive-manufacturing. Accessed 11 September 2015
14. Martukanitz RT (2014) The center for innovative materials processing through direct digital deposition (CIMP-3D)., pp 13–15, Presentation at the TTCP TP1-5 Joint Workshop, 27 February 2014, Arlington
15. NIST (2013) NIST Additive Manufacturing test artifact., NIST Engineering Laboratory, http://www.nist.gov/el/isd/sbm/amtestartifact.cfm. Accessed 10 January 2016
16. SAE (2015) SAE International to hold first Additive Manufacturing committee meeting in Atlanta., SAE International, http://www.sae.org/news/3074/. Accessed 15 September 2015
17. Maher M (2014) Open Manufacturing strategy for accelerating metals additive manufacturing. s.l., DARPA., p 2, Presentation to the 2nd MMPDS coordination meeting, Dallas. March 11, 2014
18. Kabbara J (2015) Additive Manufacturing. Federal Aviation Administration. Presented at the Gorham PMA and DER Conference 2015, San Diego, CA., pp 15–17, Available at: http://gorham-tech.com/2015_conference_documentation. Accessed 21 February 2016
19. AMAZE (2012) € 20 million project: Additive Manufacturing aiming towards zero waste & efficient production of high-tech metal products., ESA—New Materials and Energy Unit. http://www.amaze-project.eu/Accessed 24 February 2016
20. DARPA (2015) Boosting confidence in new manufacturing technologies., Defense Advanced Research Projects Agency (DARPA). http://www.darpa.mil/news-events/2015-05-29. Accessed 20 September 2015
21. Woods D (2012) Ten properties of the perfect big data storage architecture., Forbes. http://www.forbes.com/sites/danwoods/2012/07/23/ten-properties-of-the-perfect-big-data-storage-architecture/, 23 July 2012. Accessed 14 September 2015
22. EMC (2007) The expanding digital universe. In: IDC white paper, March., http://www.emc.com/leadership/digital-universe/2014iview/digital-universe-of-opportunities-vernon-turner.htm. Accessed 19 September 2015
23. Shepanek R (2010) Harnessing the power of digital data: taking the next step, scientific data management (SDM) for gov't. agencies., Report from the workshop to improve SDM, Washington. Co-sponsored by the Environmental Protection Agency (EPA), CENDI (The Federal STI Managers Group), and the Interagency Working Group on Digital Data (IWGDD)
24. Katt RJ (2013) Materials manufacturing capabilities for sustaining defense systems. National Academy of Sciences Press, Washington DC, ISBN: 978-0-309-26757-1
25. Carr D, Simmonds J (2014) Discovering data—new models proposed for effective data sharing in epidemiology., Welcome Trust, http://www.wellcome.ac.uk/News/2014/WTP056921.htm. Accessed 17 September 2015
26. Poulin M (2009) Business ecology initiative and service-oriented solution., Ebiz: The Insider's Guide to Next Generation BPM. http://www.ebizq.net/blogs/service_oriented/2009/02/evolution_of_principles_of_service_orientation_service_composability_and_discoverability_part_7.php. Accessed 20 February 2016
27. NISO (2004) Understanding metadata. National Information Standards Organization, Bethesda., p 1, NISO Press, ISBN: 1-880124-62-9. http://www.niso.org/publications/press/UnderstandingMetadata.pdf. Accessed 20 January 2016
28. NIST (2015) Managing public access to results of federally funded research., National Institutes of Technology, http://dx.doi.org/10.6028/NIST.IR.8084. Accessed 18 September 2015
29. Dublin Core (2015) Metadata innovation., The Dublin Core Metadata Initiative, http://dublincore.org/. Accessed 17 September 2015
30. DataCite (2015) DataCite., https://www.datacite.org/about-datacite/what-do-we-do. Accessed 20 September 2015
31. Research Data Alliance (2015) Research data sharing without barriers: group process & procedures., Research Data Alliance. Available via DIALOG, https://rd-alliance.org/working-and-interest-groups/group-process-procedures.html. Accessed 21 September 2015
32. DOI (2015) International DOI Foundation., http://www.doi.org/. Accessed 17 September 3015
33. Wolter R (2007) Master Data Management (MDM) Hub Architecture., Microsoft: https://msdn.microsoft.com/en-us/library/bb410798(d=printer).aspx. Accessed 23 September 2015
34. Jacobsen MD, Benedict MD, Foster BJ, Ward CH (2015) An Integrated Collaborative Environment for materials research. In: Poole W, Christensen S, Kalidindi S, Luo A, Madison J, Raabe D, Sun X (eds) Proceedings of the 3rd World Congress on Integrated Computational Materials Engineering, Colorado Springs, 31 May–4 June 2015. Wiley, Hoboken, pp 285–292
35. Reutzel E (2014) DEDatabase data definitions, Ver: 2014-01-23., p 3, Open Manufacturing program, CIMP3D, ARL, Penn State, State College
36. Zeigler W, Griffin D (2014) MSAT/MAPTIS data archiving process & material data templates & schema. Presentation, U.S. Army Research, Development and Engineering Command (ARDEC)., p 10, 28 October 2014
37. Granta (2015) Granta Design announces new solution for Additive Manufacturing data., Granta Material Intelligence. https://www.grantadesign.com/news/2015/Additive.shtml Accessed 18 September 2015
38. Granta Design (2015) GRANTA materials intelligence., Granta Design, Ltd. http://www.grantadesign.com/products/mi/am.htm. Accessed 17 September 2015
39. PWC (2014) 3D printing and the new shape of industrial manufacturing. PWC. June 2014., p 19, Available via DIALOG. http://www.pwc.com/us/en/industrial-products/assets/3d-printing-next_manufacturing-pwc.pdf Accessed 20 September 2015
40. Granta (2015) GRANTA MI:Collaborate package., Granta Material Intelligence. https://www.grantadesign.com/products/mi/collaborate.htm. Accessed 19 September 2015
41. Kelly (2014) Additive Manufacturing at EWI., EWI. https://ewi.org/eto/wp-content/uploads/2015/amcEWI716/00_Kelly.pdf. Accessed 17 September 2015
42. Stucker B (2014) Advanced modeling for Additive Manufacturing, s.l.: 3DSIM, LLC (copyright)., pp 1–24, Available via DIALOG. https://fabricationmecanique.files.wordpress.com/2014/11/3dsim-information.pdf. Accessed 18 September 2015

43. Kurzweil (2015) Open-source algorithms to enable high-quality 3D printing of metal parts., Kurzweil Accelerating Intelligence. http://www.kurzweilai.net/open-source-algorithms-to-enable-high-quality-3d-printing-of-metal-parts. Accessed 18 September 2015
44. Materials Today (2014) US$450,000 grant to develop better 3D printing simulation. In: Materials today. http://www.materialstoday.com/additive-manufacturing/news/us450000-grant-to-develop-better-3d-printing/. Accessed 18 September 2015
45. NIST (2016) NIST DSpace data entry., NIST, MatDL, Gaithersburg. https://materialsdata.nist.gov/faq/NIST_DSpace-long_tutorial.pdf. Accessed 21 February 2016.
46. MatOnto (2015) MatOnto.org., Retrieved from http://www.matonto.org/ Accessed 18 September 2015
47. iNovex (2015) iNovex Wins SBIR phase II award., iNovex Information Systems. http://www.inovexcorp.com/index.php/86-news/109-inovex-wins-sbir-award-2. Accessed 21 September 2015
48. Alhart T (2015) GE's digital marketplace to revolutionize manufacturing. In: GE Global Research., Available via DIALOG. http://www.geglobalresearch.com/news/press-releases/ges-digital-marketplace-to-revolutionize-manufacturing. Accessed 15 September 2015
49. CPS-VO (2016) DARPA VehicleFORGE., http://cps-vo.org/group/avm/vehicleforge. Accessed 20 February 2016
50. Bernardis L (2014) Structural materials data., ASM International. Available via DIALOG. http://www.asminternational.org/documents/18940848/19409350/SMDDP+Poster_060214.pdf/f3837126-8f68-427f-ab23-138950de6b0b;jsessionid=6FF2CEBB3328FD8245E744238EB4EB6D. Accessed 19 September 2015
51. Warde S (2014) GRANTA MI:Additive Manufacturing package., Granta Material Intelligence, http://www.grantadesign.com/products/mi/am.htm. Accessed 16 September 2015
52. Sher D (2014) DARPA's Open Manufacturing to fully unravel potential of metal 3D printing. In: 3D Printing Industry., http://3dprintingindustry.com/2014/08/11/3d-printing-open-manufacturing-research-program/. Accessed 18 September 2015
53. Eckerson, WW (1994) Three tier client/server architecture: achieving scalability, performance, and efficiency in client server applications. In: The Open Information Systems Journal 10(1), December, pp 1-20.

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